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OPTIMAL AND NONOPTIMAL SATISFICING I:  
A MODEL OF "SATISFACTORY" CHOICE

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**SOCIAL SCIENCE WORKING PAPER 363**

April 1981  
Revised August 1982

## OPTIMAL AND NONOPTIMAL SATISFICING II: AN EXPERIMENTAL ANALYSIS

### ABSTRACT

In this paper the authors report the results of a series of individual choice experiments designed to test the usefulness of a particular theory of satisficing and of conjunctive choice models. Several authors have argued that modeling complicated choice problems by using a conjunctive approach can provide useful simplifications. In fact optimal behavior with these models can involve implementation of extremely complicated strategies. The experiments reported deal with multidimensional search problems structured so that the conjunctive model is appropriate. Four groups of subjects performed the same tasks with similar results. In general, subjects' behavior conforms well to predictions based on optimization and where there is systematic deviation they are consistent with a specific theory of satisficing.

# OPTIMAL AND NONOPTIMAL SATISFICING II: AN EXPERIMENTAL ANALYSIS\*

David M. Grether and Louis L. Wilde

## I. INTRODUCTION

In a recent working paper, Wilde (1981) presented a new approach to the theory of satisficing, the initial observation being that the existing economics literature on satisficing seldom generates testable hypotheses because the models typically fail to include the relevant information acquisition and processing costs (see, e.g., Futia 1977; Radner 1975a, 1975b; Radner and Rothschild 1975; and Winter 1971). By including information acquisition costs, though, it is possible to characterize "optimal" satisficing strategies using the (constrained) optimization techniques familiar to all economists. Moreover, the equations which characterize the optimal satisficing strategy will then be given by a set of first-order conditions. As in most economic problems, these first-order conditions will have a marginal benefit-marginal cost interpretation.

So far, this all seems straightforward. The problem is that the optimal satisficing strategy can still be very complicated, and the whole point of satisficing rules is that they are presumed to be "easier" to use (operationalize) than optimizing rules. The question is whether there is any systematic way of simplifying the optimal satisficing strategy to make it less computationally complex.

This is where the marginal benefit-marginal cost interpretation of the first-order conditions becomes useful. It is generally possible to preserve the logic of the marginal benefit-marginal cost interpretation but simplify the calculations involved in solving the first-order conditions by ignoring certain kinds of information or interactions, yielding various "nonoptimal" satisficing strategies.

This approach to satisficing has several advantages over the existing literature. First, many nonoptimal satisficing strategies would not be evident in the absence of the formal model. Second, both the optimal satisficing strategy and the nonoptimal satisficing strategies based on it are amenable to comparative statics analysis. Thus we can test which strategy decisionmakers actually use. This highlights the third advantage; the approach makes it unnecessary to make any a priori judgments about which strategies are "easy" and which are "difficult" from a computational point of view, a problem which plagued some of the early literature on satisficing (e.g., Simon, 1955, 1972).

Wilde (1981) developed and illustrated this approach to satisficing in the context of a specific example. The purpose of this paper is to report the results of a series of laboratory experiments designed to test the theory in the context of the same example. Section II will summarize the model and illustrate the comparative statics properties of the optimal satisficing strategy and the various nonoptimal satisficing strategies based on it. Section III will

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\*The support of the National Science Foundation is gratefully acknowledged.

outline the experimental design and Section IV will summarize the results. It turned out that for the particular experiments we ran, four relatively different subject pools all conformed to one of the nonoptimal satisficing strategies, and it was the same one for all four. Section V will conclude with a further discussion of the results, and some comments on the usefulness of the exercise.

## II. THE THEORETICAL FRAMEWORK: CONJUNCTIVE CHOICE

The satisficing strategy we will use to test the theory just outlined is the so-called conjunctive choice rule. A conjunctive strategy applies to choice over multiattribute alternatives. The decisionmaker must select a cutoff (or reservation) level for each attribute and an order in which to inspect them. An item is selected from some feasible set and attributes are inspected in the specified order, with an item being rejected as soon as any attribute falls below its cutoff level.

To formalize this problem, we consider an item described by  $n$  attributes,  $x_1, \dots, x_n$ . Each attribute is assumed to have an attribute-specific inspection cost,  $c_i$ . Let the decisionmaker's underlying utility function be  $U(x_1, \dots, x_n)$  where  $\partial U / \partial x_i > 0$ . The decisionmaker is assumed to have subjective estimates of the cumulative distributions of the attributes  $F_1, \dots, F_n$ , which are independent of each other. Finally, let the cutoff level of the  $i$ 'th attribute be  $y_i$  and define  $p_i = F_i(y_i)$ .

The decisionmaker's objective is to maximize his or her

expected discounted utility net of information acquisition costs by the choice of an order of inspection and a set of cutoff levels. Sampling is without recall and the horizon is infinite. The details of this optimization problem can be found in Wilde (1981). A statement of the first-order conditions characterizing the optimal strategy will suffice for present purposes, although some notation will still be needed. Let  $W$  be the expected discounted value of following an optimal policy, and define

$$V^{i,j} = E[U(x_1, \dots, x_n) | x_{i_k} \geq y_{i_k}, k \neq j; x_{i_j} = y_{i_j}].$$

where  $\{i_1, \dots, i_n\}$  is an order of inspection. In other words,  $V^{i,j}$  gives the conditional expected utility to the decisionmaker when all attributes except the  $i_j$ 'th exceed their cutoff levels and the  $i_j$ 'th just equals its cutoff level. Then, for a given order of inspection, the following conditions define the optimal cutoff levels. For  $j = n$ ,

$$V^{i,n} - W = 0, \quad (1)$$

for  $j = n - 1$ ,

$$(V^{i,n-1} - W)(1 - p_{i_n}) = c_{i_n}, \quad (2)$$

and for all  $j \leq n - 2$

$$(V^{i,j} - W) \prod_{k=j+1}^n (1 - p_{i_k}) = c_{i_{j+1}} + \prod_{k=j+2}^n c_{i_k} \prod_{t=j+1}^{k-1} (1 - p_{i_t}). \quad (3)$$

Consider first equation (1). Here all attributes have been inspected except the last, so that the first  $n - 1$  attributes must all exceed their cutoff levels. If this were an optimizing rule,  $y_{i_n}$  would be set to take account of the actual observed values of  $x_1$  through  $x_{n-1}$ . But  $y_{i_n}$  has to be set ex ante. Hence it is set so that the ex ante expected gain from accepting the item, measured by  $V_{i_n}$ , just equals  $W$ , the value of searching again.

For the second to the last attribute, the marginal expected gain from inspecting one more attribute, in this case  $V_{i_{n-1}} - W$ , is weighted by the likelihood the item will be acceptable,  $1 - p_{i_n}$ , and compared to the marginal expected cost of observing the last attribute, in this case  $c_{i_n}$ . In general (3) reflects similar benefit-cost calculations for the remaining attributes  $i_1, \dots, i_{n-2}$ .

The ordering problem is somewhat easier to characterize. Let  $R(i) = c_i/p_i$ . Then the optimal ordering is to inspect attributes with the smallest values of  $R(i)$  first. This rule verifies the intuition that an attribute should be inspected early if it has low inspection costs or a high probability of failure—there is no point in incurring inspection costs on a number of attributes which are likely to be acceptable only to reject the item late in the game on the basis of an attribute which is cheap to inspect or unlikely to be acceptable.

Wilde (1981) also derives comparative statics for the optimal conjunctive strategy. Table 1 presents these for  $n = 3$  when  $i_1 = 1$ ,  $i_2 = 2$ , and  $i_3 = 3$ . The minus signs in parenthesis mean the

TABLE 1: Comparative Statics for the Optimal Conjunctive Strategy

	$c_1$	$c_2$	$c_3$
$y_1^*$	(-)	+	+
$y_2^*$	(-)	-	+
$y_3^*$	(-)	(-)	-

$c_i$  = sampling cost on attribute  $i$ .

$y_i^*$  = optimal cutoff level on attribute  $i$  for a risk-neutral decisionmaker.

sign is ambiguous but is likely to be negative (in fact, in our experiments we used parameters such that these were negative—see Section III).

At this point, the standard economic approach would be to test whether people behave in accord with Table 1. And they might; there is no a priori reason to believe they would not. But inspection of the first-order conditions given in (1), (2), and (3) might make one dubious, though, since they just look too complicated—they involve elements of sequentiality, simultaneity and dynamism. Sequentiality refers to the fact that, other things equal, it is more costly to discriminate on the basis of attribute  $i_j$  than  $i_k$  if  $j > k$  because rejecting a good on the basis of attribute  $j$  means that inspection costs on all attributes which precede  $j$  must be paid again. Thus, other things equal, we would expect  $y_k > y_j$ . Simultaneity refers to the fact that  $\{y_1, \dots, y_n\}$  are interdependent in the optimal satisficing strategy. Dynamism refers to the fact that the decisionmaker's objective function is defined recursively.

These are sophisticated notions. Solving (1), (2), and (3) would seem to be a relatively difficult task for a strategy which is supposed to "simplify" things. The question is what can be said about the choice of cutoff levels and an order of inspection if we abandon the optimizing model. The answer given in Wilde (1981) is to preserve the logic of (1), (2), and (3), but eliminate variously the sequential, simultaneous, and dynamic elements. For the details of this process, the reader should consult Section 4 of that paper. For

this paper we will simply illustrate the relevant comparative statics (see Tables 2 through 5).

Before turning to our experiments, a brief discussion of these comparative statics will be useful. First, the optimal strategy tells the decisionmaker that when  $c_i$  rises, he or she should search more on attributes which precede  $i$  and less on attribute  $i$  and all that follow it. Most of the nonoptimal strategies eliminate interactive effects rather than reverse them. For example, when sequentiality and simultaneity are ignored, only "own effects" remain (see Table 3). The exception is when only sequentiality is ignored, in which case the decisionmaker searches more on all attributes other than the one for which inspection costs have risen, on which he or she still searches less.

### III. EXPERIMENTAL DESIGN

The underlying structure of the conjunctive model described in Section II of this paper consists of three elements: a utility function, subjective distributions over attributes, and a set of attribute-specific inspection costs. Our experiments consisted of inducing a utility function using cash payoffs, giving subjects a set of distributions over attributes and a set of inspection costs, and then eliciting their cutoff levels. This section will describe the particulars of this process.

Subjects were recruited from social science and business classes. They were told that this was an economics experiment, that they would be paid cash at the end of the experiment (which should

TABLE 2: Comparative Statics When Sequentiality Is Ignored

	$c_1$	$c_2$	$c_3$
$y_1^*$	-	+	+
$y_2^*$	+	-	+
$y_3^*$	+	+	-

TABLE 3: Comparative Statics When Sequentiality and Simultaneity Are Ignored

	$c_1$	$c_2$	$c_3$
$y_1^*$	-	0	0
$y_2^*$	0	-	0
$y_3^*$	0	0	-

TABLE 4: Comparative Statics When Dynamic Effects Are Ignored

	$c_1$	$c_2$	$c_3$
$y_1^*$	0	(+)	(+)
$y_2^*$	0	(-)	(+)
$y_3^*$	0	0	(-)

TABLE 5: Comparative Statics When Dynamic Effects and Simultaneity Are Ignored

	$c_1$	$c_2$	$c_3$
$y_1^*$	0	+	+
$y_2^*$	0	0	+
$y_3^*$	0	0	0

$c_i$  = sampling cost on attribute  $i$ ;

$y_i^*$  = optimal cutoff level on attribute  $i$   
for a risk-neutral decisionmaker.

then eliciting their cutoff levels. This section will describe the particulars of this process.

Subjects were recruited from social science and business classes. They were told that this was an economics experiment, that they would be paid cash at the end of the experiment (which should last about an hour), and that the minimum payment would be \$5. Higher payments were possible, but could not be guaranteed. Volunteers were given slips of paper stating the time and room number of the experiment. No other information was supplied to the subjects.

During the course of the experiment random numbers were generated using a bingo cage containing balls numbered 0,1,...,9. The numbers 1 to 100 were generated by two draws with replacement; the first draw being the units digit and the second being the tens. Double zero counted as 100. One subject was chosen by lot, or election if the number of volunteers was small enough, to serve as a monitor who inspected the bingo cage and made and recorded the results of the draws from the bingo cage.

Subjects were given three types of problems, three one-attribute, six two-attribute and eight three-attribute, in that order, for a total of seventeen problems. In each case the payoff function was linear in the attributes with unitary coefficients; i.e.,  $U(x_1) = x_1$ ,  $U(x_1, x_2) = x_1 + x_2$ , and  $U(x_1, x_2, x_3) = x_1 + x_2 + x_3$ , respectively, for the three types of problems. Subjects were informed at the outset of the experiment that they would be rewarded on the basis of their choices for one of the seventeen problems, to be

were told objectively how the values of attributes were determined (using the bingo cage), that their task was to set cutoff level(s), and that their payment would be the value of the attributes less the cost of generating those values and the cost of generating the values which were rejected because they were below the stated cutoffs.

Initially, subjects were given written instructions covering the one-attribute problem only. After reading the instructions to the subjects and answering any questions, an example showing how to calculate payoffs was done on the blackboard. Once subjects appeared to understand the task they each chose cutoffs for a one-attribute problem. When finished, this problem was "run off" at once; i.e., numbers were generated and each subject computed what his or her earnings would be from this problem if it happened to be the one that determined payment. Subjects then chose cutoffs for two additional one-attribute problems. These problems were included as a training device and are not further discussed here. Procedures for the two-attribute problems were identical, including the actual calculation of earnings by each subject for the first of these problems. Subjects appeared to quickly grasp the sequential element present in these problems. They were told that numbers would be drawn until they had at least equaled their cutoffs on the first attribute. Then a single draw would be made for the second attribute. If the number exceeded their cutoff on the second attribute, they were done and should calculate their earnings. Otherwise, they would have to start over beginning with the first attribute. After the two-attribute problems

were completed, the three-attribute problems were introduced. No three-attribute problems were "run off" unless one was selected to determine earnings, as the two-attribute problems clearly indicated the sequential nature of the multiattribute problems.

Table 6 gives the parameters we used for the two-attribute problems and Table 7 gives the parameters we used for the three-attribute problems. In these tables  $\sum X_1$ ,  $\sum X_2$ , and  $\sum X_3$  refer to the supports of the distribution of  $X_1$ ,  $X_2$ , and  $X_3$  respectively (recall that in our experiments all distributions were uniform on their support). The tables also show the optimal values of the cutoff levels for each problem assuming decisionmakers are risk neutral ( $y_1^*$ ,  $y_2^*$ , or  $y_3^*$ ). For each class of problem (two- or three-attribute) there are two types, those in which attributes had common supports and those in which they had different supports. In each case, just enough variations were included to compute the comparative statics necessary to test the theory outlined in Section II. The parameters were selected so that changes in the costs of sampling should lead to fairly large changes in the cutoff levels.

This choice of problems also allowed us to test the ordering part of the conjunctive strategy. After all the choices had been made, but before determination of the problem upon which rewards were to be based, subjects were told they could choose their most preferred problem among certain subsets. If any member of the subset was selected as the one on which rewards were to be based, the one they chose would be used. The subsets were {2A.2, 2A.3}, {3A.2, 3A.3,



TABLE 6: Parameter Values for the Two-Attribute Problems and Optimal Cutoffs for Wealth-Maximizing Strategies

Type 2A:  $\sum x_1 = [1,11], \sum x_2 = [1,11]$ 

#	$c_1$	$c_2$	$y_1^*$	$y_2^*$
1	.25	.25	7.65	6.53
2	2.00	.25	3.84	3.20
3	.25	2.00	8.46	3.28

Type 2B:  $\sum x_1 = [3,8], \sum x_2 = [4,12]$ 

#	$c_1$	$c_2$	$y_1^*$	$y_2^*$
1	.10	.10	6.20	9.54
2	1.50	.10	3.17	6.86
3	.10	2.50	6.92	5.11

 $c_i$  = sampling cost on attribute  $i$ . $y_i^*$  = optimal cutoff level on attribute  $i$  for a risk-neutral decisionmaker.

TABLE 7: Parameter Values for the Three Attribute Problems and Optimal Cutoffs for Wealth-Maximizing Strategies

Type 3A:  $\sum x_1 = [0,8], \sum x_2 = [0,8], \sum x_3 = [0,8]$ 

#	$c_1$	$c_2$	$c_3$	$y_1^*$	$y_2^*$	$y_3^*$
1	.10	.10	.10	5.32	4.42	4.02
2	2.00	.10	.10	1.46	1.19	.97
3	.10	2.00	.10	6.54	1.19	.96
4	.10	.10	2.00	5.77	5.15	.74

Type 3B:  $\sum x_1 = [0,5], \sum x_2 = [0,10], \sum x_3 = [0,10]$ 

#	$c_1$	$c_2$	$c_3$	$y_1^*$	$y_2^*$	$y_3^*$
1	.10	.10	.10	2.49	6.24	5.77
2	.75	.10	.10	.15	4.52	4.18
3	.10	3.50	.10	3.92	.81	.60
4	.10	.10	3.50	3.06	7.30	.18

 $c_i$  = sampling cost on attribute  $i$ . $y_i^*$  = optimal cutoff level on attribute  $i$  for a risk-neutral decisionmaker.

3A.4), and {3B.2, 3B.3, 3B.4} (see Tables 6 and 7). The first two of these provide a pure test of the ordering problem since the distributions have common supports and the inspection costs, when they are raised, are all raised to a common value. The third problem has different supports and different costs. It therefore tests whether subjects are sensitive to the trade-off between high costs and high cutoff levels in selecting orderings.

#### IV. EXPERIMENTAL RESULTS

Tables 8 and 9 give the mean cutoffs for each school for the two- and three-attribute problems. Full summary statistics—means, variances, and t-statistics—for assessing differences are given in the Appendix.

Comparing the first and second rows of Table 8 we see that for every group the amount of search on the first dimension dropped on average when the cost of search for that dimension rose. Comparing the first and third rows shows that in general when the cost of searching the second dimension rose, subjects tended to search less on that dimension. The sole exception to this was the Pasadena City College group on the problem with unequal intervals. Further inspection of the table suggests that the effects of changing the cost of inspection on one dimension on the cutoffs placed on the other dimension is more mixed, in fact, hardly systematic at all.

Table 10 summarizes the observed comparative statics results for the two-attribute problems. A "+" or "-" shown in parentheses

means that the direction of the change is as indicated, but that it failed to be significant at the 5 percent level. As the data are constrained to lie in fixed intervals and are clearly nonnormal (e.g., several subjects adopted highly risk averse strategies, placing their cutoffs on or near the minimum points of the intervals), relying on t-statistics may be misleading. This problem can be alleviated simply by counting the number of individuals that raised, lowered, or did not change their cutoff levels (see the appendix for these data). Table 11 gives the significance level at which the hypothesis of random behavior is rejected. It is clear that if one bases the judgment of the comparative statics on these figures the conclusions are substantially unaltered.

Conclusion 1. In two-attribute problems, when the cost of searching a dimension is increased, subjects search less on that dimension.

Conclusion 2. In two-attribute problems, when the cost of search is raised on one dimension, the effect upon search behavior for the other dimensions is not systematic.

Thus, we have

Conclusion 3. For the two-attribute problems, the observed results correspond to the comparative statics prediction when subjects ignore sequentiality and simultaneity.

Inspection of Table 9 shows that the same general patterns hold for the three-attribute problems as well. Without exception when

TABLE 8  
SUMMARY RESULTS FOR TWO-ATTRIBUTE EQUAL INTERVALS PROBLEMS

$$\sum x_1 = [1,11] \quad \sum x_2 = [1,11]$$

$c_1$	$c_2$	$y_1^*$	$y_2^*$	MTSAC		PCC		CSUN		UCLA	
				$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_1$	$\bar{y}_2$
.10	.10	7.65	6.53	6.49	4.90	6.56	4.67	7.38	5.11	7.28	4.62
2.00	.10	3.84	3.20	4.82	3.87	5.01	5.24	4.46	5.32	4.88	4.35
.10	2.00	8.46	3.28	5.80	3.57	7.31	4.37	7.57	3.09	7.06	3.54

SUMMARY RESULTS FOR TWO-ATTRIBUTE UNEQUAL INTERVALS PROBLEMS

$$\sum x_1 = [3,8] \quad \sum x_2 = [4,12]$$

$c_1$	$c_2$	$y_1^*$	$y_2^*$	MTSAC		PCC		CSUN		UCLA	
				$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_1$	$\bar{y}_2$
.10	.10	6.20	9.54	5.58	5.68	5.61	6.72	6.13	7.35	6.24	7.07
1.50	.10	3.17	6.86	4.97	5.70	4.60	5.95	4.62	7.00	4.85	6.47
.10	2.50	6.92	5.11	5.75	5.83	5.51	6.00	6.34	5.56	6.13	5.73

$c_i$  = cost per observation on attribute i.

$y_i^*$  = wealth-maximizing cutoff level for attribute i.

$\bar{y}_i$  = average actual cutoff level for attribute i.

TABLE 9

## SUMMARY RESULTS FOR THREE-ATTRIBUTE EQUAL INTERVALS PROBLEMS

$$\sum x_1 = [0,8] \quad \sum x_2 = [0,8] \quad \sum x_3 = [0,8]$$

$c_1$	$c_2$	$c_3$	$y_1^*$	$y_2^*$	$y_3^*$	MTSAC			PCC			CSUN			UCLA		
						$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_3$	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_3$	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_3$	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_3$
.10	.10	.10	5.32	4.42	4.02	3.88	2.93	2.44	4.69	3.39	3.27	5.08	4.00	3.16	5.36	3.95	3.75
2.00	.10	.10	1.46	1.19	.97	3.06	2.77	2.79	2.99	2.88	2.72	2.85	3.43	2.83	2.86	3.56	3.22
.10	2.00	.10	6.54	1.19	.97	2.93	2.45	2.60	4.68	2.49	2.73	5.12	2.03	2.61	5.21	2.42	3.17
.10	.10	2.00	5.77	5.15	.74	3.96	3.24	2.43	4.69	3.31	2.25	5.25	3.66	1.79	5.22	3.93	1.90

## SUMMARY RESULTS FOR THREE-ATTRIBUTE UNEQUAL INTERVALS PROBLEMS

$$\sum x_1 = [0,5] \quad \sum x_2 = [0,10] \quad \sum x_3 = [0,10]$$

$c_1$	$c_2$	$c_3$	$y_1^*$	$y_2^*$	$y_3^*$	MTSAC			PCC			CSUN			UCLA		
						$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_3$	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_3$	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_3$	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_3$
.10	.10	.10	2.49	6.24	5.77	2.55	3.50	3.73	2.76	4.11	4.15	3.11	4.90	3.78	3.06	5.23	4.38
.75	.10	.10	.15	4.52	4.18	2.40	3.74	2.96	2.24	3.99	3.56	2.17	4.94	4.17	2.46	4.61	4.16
.10	3.50	.10	3.92	.81	.60	2.58	2.71	3.16	2.54	2.99	3.13	3.06	2.29	2.97	3.04	3.00	3.79
.10	.10	3.50	3.06	7.30	.18	2.52	3.25	2.63	2.69	4.18	2.75	2.60	4.73	2.16	3.05	5.20	2.40

$c_i$  = cost per observation on attribute  $i$ .

$y_i^*$  = wealth-maximizing cutoff level for attribute  $i$ .

$\bar{y}_i$  = average actual cutoff level for attribute  $i$ .

TABLE 10: Observed Comparative Statics Results

$$2A: \sum x_1 = [1,11], \sum x_2 = [1,11]$$

MTSAC			PCC		
	$\Delta c_1$	$\Delta c_2$		$\Delta c_1$	$\Delta c_2$
$\Delta \bar{y}_1$	-	(-)	$\Delta \bar{y}_1$	(-)	(+)
$\Delta \bar{y}_2$	-	-	$\Delta \bar{y}_2$	(+)	(-)
CSUN			UCLA		
	$\Delta c_1$	$\Delta c_2$		$\Delta c_1$	$\Delta c_2$
$\Delta \bar{y}_1$	-	(+)	$\Delta \bar{y}_1$	-	(+)
$\Delta \bar{y}_2$	(+)	-	$\Delta \bar{y}_2$	(-)	-

$$2B: \sum x_1 = [3,8], \sum x_2 = [4,12]$$

MTSAC			PCC		
	$\Delta c_1$	$\Delta c_2$		$\Delta c_1$	$\Delta c_2$
$\Delta \bar{y}_1$	-	(+)	$\Delta \bar{y}_1$	-	(-)
$\Delta \bar{y}_2$	(+)	(+)	$\Delta \bar{y}_2$	(-)	(-)
CSUN			UCLA		
	$\Delta c_1$	$\Delta c_2$		$\Delta c_1$	$\Delta c_2$
$\Delta \bar{y}_1$	-	(+)	$\Delta \bar{y}_1$	-	(+)
$\Delta \bar{y}_2$	(-)	-	$\Delta \bar{y}_2$	(-)	-

$c_i$  = sampling cost on attribute  $i$ ;

$\bar{y}_i$  = average cutoff level on attribute  $i$ .

TABLE 11: Tail Probabilities for  
Two-Attribute Comparative Statistics

Decision 2A				
Group	$\Delta c_1$		$\Delta c_2$	
	$\bar{\Delta y}_1$	$\bar{\Delta y}_2$	$\bar{\Delta y}_1$	$\bar{\Delta y}_2$
MTSAC	<u>.0003</u>	.0013	.0946	<u>.0000</u>
PCC	<u>.0610</u>	.6612	.9738	<u>.7728</u>
CSUN	<u>.0000</u>	.8204	.7483	<u>.0022</u>
UCLA	<u>.0000</u>	.0717	.0436	<u>.0000</u>
Decision 2B				
Group	$\Delta c_1$		$\Delta c_2$	
	$\bar{\Delta y}_1$	$\bar{\Delta y}_2$	$\bar{\Delta y}_1$	$\bar{\Delta y}_2$
MTSAC	<u>.0466</u>	.6762	.7383	<u>.6762</u>
PCC	<u>.0013</u>	.0835	.0287	<u>.2517</u>
CSUN	<u>.0000</u>	.1662	.6128	<u>.0001</u>
UCLA	<u>.0000</u>	.0121	.5775	<u>.0000</u>

Probability of as many or more reductions in cutoff levels.  
Assumes  $p = 1/2$ . Gives significance level at which the null  
hypothesis is rejected.

$c_i$  = sampling cost on attribute  $i$

$\bar{y}_i$  = average cutoff level on attribute  $i$ .

the costs of searching a dimension are raised, subjects search less on that dimension. As with the two-attribute problems the results on "cross-effects" are mixed. The observed comparative statics results are displayed in Table 12, and the rejection probabilities for calculations based on changes in cutoffs only are presented in Table 13. Both sets of statistics lead to basically the same conclusion; i.e., subjects responded to the three-attribute problems in the same quantitative way as to the two-attribute problems.

Conclusion 4. In three-attribute problems, subjects respond by searching less on a dimension when the cost of searching it increases, though the responses in terms of the cutoff levels for the other dimension is not systematic.

Conclusion 5. In three-attribute problems, subjects behaved as if they were ignoring sequentiality and simultaneity.

We have seen that in terms of comparative statics the subjects in these experiments behaved in a quite systematic fashion. In addition, their performance conformed well with predictions based upon optimizing behavior in other ways. For example, when the costs of search are equal and the intervals are of equal length, the wealth-maximizing strategy calls for most searching on the first dimension, less on the second, and for three-attribute problems, least on the third dimension. From Tables 14 and 15 one can see that in fact subjects in all groups tended to order their cutoffs as predicted by theory far more often than could reasonably be expected by chance.

TABLE 12: Observed Comparative Statics Results

3A:  $\sum x_1 = [0,8], \sum x_2 = [0,8], \sum x_3 = [0,8]$

MTSAC			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\Delta \bar{y}_1$	-	(+)	(+)
$\Delta \bar{y}_2$	(-)	(-)	(+)
$\Delta \bar{y}_3$	(+)	(+)	(-)
CSUN			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\Delta \bar{y}_1$	-	(+)	(+)
$\Delta \bar{y}_2$	(-)	-	(-)
$\Delta \bar{y}_3$	(-)	(-)	-

PCC			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\Delta \bar{y}_1$	-	(-)	(+)
$\Delta \bar{y}_2$	(-)	-	(-)
$\Delta \bar{y}_3$	(-)	(-)	-
UCLA			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\Delta \bar{y}_1$	-	(-)	(-)
$\Delta \bar{y}_2$	(-)	-	(-)
$\Delta \bar{y}_3$	(-)	(-)	-

3B:  $\sum x_1 = [0,5], \sum x_2 = [0,10], \sum x_3 = [0,10]$

MTSAC			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\Delta \bar{y}_1$	(-)	(+)	(+)
$\Delta \bar{y}_2$	(+)	-	(-)
$\Delta \bar{y}_3$	(-)	(-)	-
CSUN			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\Delta \bar{y}_1$	-	(-)	(-)
$\Delta \bar{y}_2$	(+)	-	(-)
$\Delta \bar{y}_3$	(+)	(-)	-

PCC			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\Delta \bar{y}_1$	-	(-)	(-)
$\Delta \bar{y}_2$	(-)	-	(+)
$\Delta \bar{y}_3$	(-)	-	-
UCLA			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\Delta \bar{y}_1$	-	(-)	(+)
$\Delta \bar{y}_2$	(-)	-	(+)
$\Delta \bar{y}_3$	(-)	(-)	-

$c_i$  = sampling cost on attribute  $i$ ;

$\bar{y}_i$  = average cutoff level on attribute  $i$ .

TABLE 13: Tail Probabilities for  
Three-Attribute Comparative Statistics

Decision 3A									
Group	$\Delta c_1$			$\Delta c_2$			$\Delta c_3$		
	$\Delta \bar{y}_1$	$\Delta \bar{y}_2$	$\Delta \bar{y}_3$	$\Delta \bar{y}_1$	$\Delta \bar{y}_2$	$\Delta \bar{y}_3$	$\Delta \bar{y}_1$	$\Delta \bar{y}_2$	$\Delta \bar{y}_3$
MTSAC	<u>.0378</u>	.5000	.5881	.9054	<u>.0173</u>	.3238	.5841	.9915	<u>.1431</u>
PCC	<u>.0053</u>	.1796	.0577	.5000	<u>.0835</u>	.3238	.1334	.7597	<u>.0318</u>
CSUN	<u>.0000</u>	.2272	.3145	.2905	<u>.0022</u>	.1662	.5000	.1662	<u>.0007</u>
UCLA	<u>.0000</u>	.1077	.0003	.0026	<u>.0000</u>	.0057	.0758	.5000	<u>.0000</u>
Decision 3B									
Group	$\Delta c_1$			$\Delta c_2$			$\Delta c_3$		
	$\Delta \bar{y}_1$	$\Delta \bar{y}_2$	$\Delta \bar{y}_3$	$\Delta \bar{y}_1$	$\Delta \bar{y}_2$	$\Delta \bar{y}_3$	$\Delta \bar{y}_1$	$\Delta \bar{y}_2$	$\Delta \bar{y}_3$
MTSAC	<u>.1917</u>	.9331	.0946	.5841	<u>.0843</u>	.5000	.4119	.5000	<u>.0320</u>
PCC	<u>.0835</u>	.7228	.0592	.3036	<u>.0669</u>	.0946	.6964	.6964	<u>.0392</u>
CSUN	<u>.0001</u>	.3953	.6964	.3953	<u>.0000</u>	.0176	.0287	.8491	<u>.0064</u>
UCLA	<u>.0026</u>	.0251	.0401	.4159	<u>.0001</u>	.0147	.5000	.7142	<u>.0000</u>

Probability of as many or more reductions in cutoff levels. Assumes  $p = 1/2$ .  
Gives significance level at which the null hypothesis is rejected.

$c_i$  = sampling cost on attribute  $i$

$\bar{y}_i$  = average cutoff level on attribute  $i$ .



TABLE 14: Ordering of Individual Cutoff Levels  
(Equal Intervals and Equal Costs)

Two Attributes					
Group	(1) $y_1 > y_2$	(2) $y_1 = y_2$	(3) $y_1 < y_2$	Probability of at Least as Many $y_1 > y_2$	
				$p = 1/3$	$p = 1/2$
MTSAC	20	6	7	.0012	.0096
PCC	15	12	3	.0435	.0038
CSUN	17	2	3	.0000	.0013
UCLA	36	5	2	.0000	.0000
Total*	88	25	15		

\*Based on the null hypothesis that  $p = 1/3$ ,  $t = 8.5$ .

Based on the null hypothesis that  $p = 1/2$ ,  $t = 7.2$ .

TABLE 15: Ordering of Individual Cutoff Levels  
(Equal Intervals and Equal Costs)

Three Attributes					
Group	(1)* $y_1 > y_2 > y_3$	(2)** $y_1 > y_2$	(3)** $y_1 > y_3$	(4)** $y_2 > y_3$	(5)*** $y_1 > y_2 = y_3$
MTSAC	18	10	9	3	6
PCC	17	6	5	2	4
CSUN	7	8	8	2	6
UCLA	17	11	11	3	6
Total	59	35	33	10	22

\*Based on the null hypothesis that  $p = 1/13$ ,  $t = 16.3$ .

\*\*Counts in addition to those shown in column 1. Based on the null hypothesis that  $p = 1/3$ , for

$y_1 > y_2$ ,  $t = 9.6$ ;

$y_1 > y_3$ ,  $t = 9.2$ ;

$y_2 > y_3$ ,  $t = 4.9$ .

\*\*\*Also counted in columns 2 and 3.

Finally, we consider the choice of which attribute to search first. As explained in the previous section, we did not allow subjects to make this choice directly as we thought it might make an already complicated problem confusing. Instead we offered subjects the choice (within certain sets) of which problem they would prefer to use for determining their payments. For the two-attribute equal-interval problems, for example, the choice between the cost pattern (.10, 2.50) and (2.50, .10) in effect allows subjects to choose whether they would rather search the high cost dimension first or last (as predicted by theory). Table 16 provides some summary data on these choices.

The results on orderings are quite interesting. Between 2A.2 and 2A.3, an expected income-maximizing decisionmaker behaving optimally would pick 2A.3; between 3A.2, 3A.3 and 3A.4, he or she would pick 3A.4; and between 3B.2, 3B.3 and 3B.4, he or she would pick 3B.2. The last problem is the difficult one since a decisionmaker ordering on the basis of cost alone would pick 3B.4. Table 16 shows that performance was again sensitive to the subject pool, even more so than with cutoff levels. On individual problems, the Mt. San Antonio College (MTSAC) group did not do so well. We did not give the Pasadena City College (PCC) group this problem, but the California State University at Northridge (CSUN) group did well on the easy problems and not so well on the hard one. The University of California at Los Angeles (UCLA) group did well on all, splitting roughly evenly on the two strategies for 3B.

Looking across the three ordering problems, we can track individuals and test whether significant numbers did well on more than one. Table 17 gives these results. We consider subjects who got both easy problems right, those who got all three problems right, and those who got the easy problems right but used the "high-cost last" rule on the hard problem. Again, performance improved as we moved from MTSAC to CSUN to UCLA. Overall, highly significant numbers of people appeared to understand either the wealth-maximizing strategy or the high-cost last strategy, especially among the more quantitatively sophisticated group.

If we evaluate choices on the basis of the actual cutoff levels set by subjects we get slightly different results. If anything, subjects did worse on the basis of actual cutoffs, suggesting they might have a better "feel" for the ordering problem than the cutoff problem, although even this is a tenuous conclusion.

## V. SUMMARY AND CONCLUSIONS

In this paper we have presented the results of a series of experiments designed to test the ability of people to adopt conjunctive choice strategies. This is an important area of research, as many writers, especially in the marketing literature, have suggested the conjunctive strategy as a useful simplifying device for consumers facing complicated choice problems.

This last observation raises the learning issue. Our primary objective in these experiments was to implement the theory of satisficing presented in Wilde (1981). However, we were also

TABLE 16: Individual Choices of Problems for Payment (Theoretical Cutoffs)

Group	2A.2 and 2A.3				3A.2, 3A.3, and 3A.4			
	N	# Right	P*	t	N	# Right	P*	t
MTSAC	27	16	.221	0.96	30	15	.044	1.94
CSUN	22	17	.009	2.56	21	16	.000	4.17
UCLA	42	32	.001	3.39	43	31	.000	5.39
Group	(Wealth-Maximizing Strategy) 3B.2, 3B.3, and 3B.4				(High-Cost Last Strategy) 3B.2, 3B.3, and 3B.4			
	N	# Right	P*	t	N	# Right	P*	t
MTSAC	33	12	.419	0.37	33	10	.565	-0.37
CSUN	22	8	.293	0.30	22	9	.163	0.75
UCLA	43	21	.012	2.16	43	19	.050	1.51

\*Probability of at least as many right, assuming choice of problems is to be equally likely.

TABLE 17: Individual Choices on Groups of Problems for Payment

Group	2A and 3A				(Wealth-Maximizing Strategy) 2A, 3A, and 3B			
	N	# Right	P*	t	N	# Right	P*	t
MTSAC	27	11	.003	3.36	27	1	.786	-0.42
CSUN	21	14	.000	6.15	21	6	.001	4.60
UCLA	42	26	.000	7.87	42	11	.000	5.84

  

Group	(High-Cost Last Strategy) 2A, 3A, and 3B			
	N	# Right	P*	t
MTSAC	27	6	.003	3.78
CSUN	21	5	.005	3.65
UCLA	42	15	.000	8.53

\*Probability of at least as many right, assuming choice of problems is to be equally likely.

interested in understanding the extent to which people grasp the nature of the conjunctive choice rule at a more or less intuitive level. During the last decade, there has been a growing belief among consumer researchers that the conjunctive rule is often used as an initial screening device in complex choice situations (see Bettman [1979] for a discussion of this research). If this is true then it is clearly important to understand whether people use the rule "properly" and, if they do not, the nature of their difficulties with it. We shall discuss the implications of our experiments for consumer research elsewhere but an obvious question is whether performance might not improve with familiarity. The likely answer to this question is yes. The more significant questions are by how much and in what ways. If the changes in performance as we move from MTSAC to PCC to CSUN to UCLA are any indication, it appears reasonable to conjecture that improvements due to familiarity are likely to be statistically significant but not qualitatively significant. There is an obvious set of experiments which could test this conjecture, but we have not as yet run them.

The learning issue also is important in the context of the theory of satisficing these experiments are meant to test. A traditional, market-oriented economist would reject all theories of satisficing as irrelevant since learning behavior, conditioned by the discipline of the market, will ultimately make agents act as if they are maximizing. This makes more sense in the theory of the firm than in the theory of consumer behavior, but even there it misses the

point. If agents fail to optimize because of computation costs, then learning or familiarity with a problem should not change the qualitative behavior of agents unless it reduces those costs. What it is likely to do is make agents perform better at whatever nonoptimal level they chose to locate. In other words, it should reduce the variance in their behavior but not change its qualitative nature. This is, in fact, precisely what we saw in these experiments.

Overall, our results are quite striking. First, the behavior of people without prior training corresponds in several ways to predictions based on optimizing behavior. Thus, as the cost of inspecting a dimension increases, people tend to search less on that dimension. For two- and three-attribute goods the rankings across attributes of the intensity of search correspond to the prediction of optimization. Also, the order in which attributes are inspected is as it would be if the order were chosen in order to maximize expected return (strictly speaking we infer this latter conclusion from responses to a closely related question).

Additionally, when the observed behavior differed with strict optimizing behavior, the differences were uniform across subject pools and corresponded roughly to a simple satisficing strategy. That is, subjects in our experiments responded to changing costs of information as if they had simplified the first-order conditions to make them easier to handle. Specifically, the behavior suggests that when responding to change in information costs the subjects ignored the sequential and simultaneous aspects of the solution.

In summary, individuals without prior training perform quite well when using the conjunctive strategy. By this we mean their performance corresponds well with the prediction of optimization. When the problem is changed and they must respond, their behavior is consistent with the use of some straightforward rules of thumb. Thus, it is reasonable to suppose that economic agents might use conjunctive strategies in decisionmaking. Also, we have presented evidence of quite sophisticated behavior on the part of subjects from a variety of backgrounds who were dealing with an extremely complicated decision problem.

## APPENDIX

TABLE 18: t-Statistics for Comparative Statics

$$2A: \sum X_1 = [1,11], \sum X_2 = [1,11]$$

MTSAC			PCC		
	$\Delta c_1$	$\Delta c_2$		$\Delta c_1$	$\Delta c_2$
$\bar{\Delta y}_1$	3.10	1.15	$\bar{\Delta y}_1$	2.19	1.04
$\bar{\Delta y}_2$	1.84	.14	$\bar{\Delta y}_2$	.78	.44
CSUN			UCLA		
	$\Delta c_1$	$\Delta c_2$		$\Delta c_1$	$\Delta c_2$
$\bar{\Delta y}_1$	5.43	.32	$\bar{\Delta y}_1$	4.84	.46
$\bar{\Delta y}_2$	.29	3.14	$\bar{\Delta y}_2$	.52	2.19

$$2B: \sum X_1 = [3,8], \sum X_2 = [4,12]$$

MTSAC			PCC		
	$\Delta c_1$	$\Delta c_2$		$\Delta c_1$	$\Delta c_2$
$\bar{\Delta y}_1$	1.88	.59	$\bar{\Delta y}_1$	3.08	.28
$\bar{\Delta y}_2$	.04	.33	$\bar{\Delta y}_2$	1.34	1.24
CSUN			UCLA		
	$\Delta c_1$	$\Delta c_2$		$\Delta c_1$	$\Delta c_2$
$\bar{\Delta y}_1$	4.19	.51	$\bar{\Delta y}_1$	5.56	.40
$\bar{\Delta y}_2$	1.22	3.94	$\bar{\Delta y}_2$	1.29	3.10

$c_i$  = sampling cost on attribute  $i$

$\bar{y}_i$  = average cutoff level on attribute  $i$

TABLE 19: t-Statistics for Comparative Statics

$$3A: \sum X_1 = [0,8], \sum X_2 = [0,8], \sum X_3 = [0,8]$$

MTSAC			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\bar{\Delta y}_1$	1.51	.10	.15
$\bar{\Delta y}_2$	.36	1.07	.66
$\bar{\Delta y}_3$	.72	.35	.03
CSUN			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\bar{\Delta y}_1$	3.71	.06	.25
$\bar{\Delta y}_2$	.95	3.71	.56
$\bar{\Delta y}_3$	.55	.88	2.39

PCC			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\bar{\Delta y}_1$	2.92	.01	.01
$\bar{\Delta y}_2$	.91	1.70	.14
$\bar{\Delta y}_3$	1.00	.94	1.83
UCLA			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\bar{\Delta y}_1$	6.06	.35	.32
$\bar{\Delta y}_2$	.95	3.82	.05
$\bar{\Delta y}_3$	1.17	1.35	4.58

$$3B: \sum X_1 = [0,5], \sum X_2 = [0,10], \sum X_3 = [0,10]$$

MTSAC			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\bar{\Delta y}_1$	.44	.07	.11
$\bar{\Delta y}_2$	.40	1.46	.48
$\bar{\Delta y}_3$	1.15	.85	1.69
CSUN			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\bar{\Delta y}_1$	2.15	.11	1.09
$\bar{\Delta y}_2$	.06	3.50	.20
$\bar{\Delta y}_3$	.48	1.00	2.10

PCC			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\bar{\Delta y}_1$	1.43	.60	.21
$\bar{\Delta y}_2$	.16	1.51	.10
$\bar{\Delta y}_3$	.79	1.37	1.87
UCLA			
	$\Delta c_1$	$\Delta c_2$	$\Delta c_3$
$\bar{\Delta y}_1$	2.15	.09	.03
$\bar{\Delta y}_2$	1.16	4.43	.04
$\bar{\Delta y}_3$	.41	1.05	4.17

$c_i$  = sampling cost on attribute  $i$ ;  $\bar{y}_i$  = average cutoff level on attribute  $i$

TABLE 20: t-Statistics for Decreasing Cutoff Levels

$$2A: \sum X_1 = [1,11], \sum X_2 = [1,11]$$

Group	$\bar{y}_1$ vs $\bar{y}_2$
MTSAC	2.63
PCC	2.70
CSUN	3.81
UCLA	5.20

$$3A: \sum X_1 = [0,8], \sum X_2 = [0,8], \sum X_3 = [0,8]$$

Group	$c_1 = .10, c_2 = .10, c_3 = .10$	
	$\bar{y}_1$ vs $\bar{y}_2$	$\bar{y}_2$ vs $\bar{y}_3$
MTSAC	1.85	1.09
PCC	2.26	.21
CSUN	1.77	1.37
UCLA	3.26	.46

$c_i$  = sampling cost on attribute  $i$

$\bar{y}_i$  = average cutoff level on attribute  $i$

TABLE 21. Complete Summary Results for Two-Attribute Equal Intervals Problems: Means and Variances of Observed Cutoff Levels

$$2.A: \sum X_1 = [1,11], \sum X_2 = [1,11]$$

#	N	$c_1$	$c_2$	$\bar{y}_1$	$\bar{y}_2$	$\sigma_1^2$	$\sigma_2^2$
MTSAC							
1	33	.25	.25	6.49	4.90	5.28	6.38
2	33	2.00	.25	4.82	3.87	4.06	3.48
3	33	.25	2.00	5.80	3.57	6.05	5.00
PCC							
1	30	.25	.25	6.56	4.67	7.16	7.09
2	30	2.00	.25	5.01	5.24	7.24	8.23
3	30	.25	2.00	7.31	4.37	8.08	6.76
CSUN							
1	22	.25	.25	7.38	5.11	2.48	4.98
2	22	2.00	.25	4.46	5.32	3.57	6.25
3	22	.25	2.00	7.57	3.09	4.96	3.85
UCLA							
1	43	.25	.25	7.28	4.62	5.03	5.95
2	43	2.00	.25	4.88	4.35	5.25	5.91
3	43	.25	2.00	7.06	3.54	4.21	4.19

$c_i$  = sampling cost on attribute i

$\bar{y}_i$  = average cutoff level on attribute i

$\sigma_i^2$  = sample variance

TABLE 22. Complete Summary Results for Two-Attribute Unequal Intervals Problems: Means and Variances of Observed Cutoff Levels

$$2.B: \sum X_1 = [3,8], \sum X_2 = [4,12]$$

#	N	$c_1$	$c_2$	$\bar{y}_1$	$\bar{y}_2$	$\sigma_1^2$	$\sigma_2^2$
MTSAC							
1	32	.10	.10	5.54	5.68	1.62	3.05
2	32	1.50	.10	4.97	5.70	1.26	2.80
3	32	.10	2.50	5.75	5.83	2.34	3.42
PCC							
1	30	.10	.10	5.61	6.72	1.76	5.42
2	30	1.50	.10	4.60	5.95	1.36	4.19
3	30	.10	2.50	5.51	6.00	2.04	4.30
CSUN							
1	22	.10	.10	6.13	7.75	2.04	4.22
2	22	1.50	.10	4.62	7.00	.69	3.67
3	22	.10	2.50	6.34	5.56	1.68	2.24
UCLA							
1	43	.10	.10	6.24	7.07	1.50	4.69
2	43	1.50	.10	4.85	6.47	1.19	4.11
3	43	.10	2.50	6.13	5.73	1.47	3.09

$c_i$  = sampling cost on attribute i

$\bar{y}_i$  = average cutoff level on attribute i

$\sigma_i^2$  = sample variance



TABLE 23. Complete Summary Results for Three-Attribute Equal Intervals Problems: Means and Variance of Observed Cutoff Levels

$$3.A: \sum X_1 = [0,8], \sum X_2 = [0,8], \sum X_3 = [0,8]$$

#	N	c <sub>1</sub>	c <sub>2</sub>	c <sub>3</sub>	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_3$	$\sigma_1^2$	$\sigma_2^2$	$\sigma_3^2$
MTSAC										
1	33	.10	.10	.10	3.88	2.93	2.44	4.99	3.47	3.01
2	33	2.00	.10	.10	3.06	2.77	2.79	4.43	2.74	4.37
3	33	.10	2.00	.10	2.93	2.45	2.60	4.54	2.85	3.51
4	33	.10	.10	2.00	3.96	3.24	2.43	4.27	3.71	3.90
PCC										
1	30	.10	.10	.10	4.69	3.39	3.27	4.91	4.68	4.77
2	30	2.00	.10	.10	2.99	2.88	2.72	4.88	4.26	4.05
3	30	.10	2.00	.10	4.68	2.49	2.73	6.26	3.38	4.69
4	30	.10	.10	2.00	4.69	3.31	2.25	5.35	4.77	4.18
CSUN										
1	22	.10	.10	.10	5.08	4.00	3.16	4.19	3.66	4.22
2	22	2.00	.10	.10	2.85	3.43	2.83	3.38	4.06	3.19
3	22	.10	2.00	.10	5.12	2.03	2.61	4.90	2.29	3.99
4	22	.10	.10	2.00	5.25	3.66	1.79	6.05	4.23	2.70
UCLA										
1	43	.10	.10	.10	5.36	3.95	3.75	4.14	3.72	4.39
2	43	2.00	.10	.10	2.86	3.56	3.22	2.99	3.52	4.33
3	43	.10	2.00	.10	5.21	2.42	3.17	3.47	3.04	3.44
4	43	.10	.10	2.00	5.22	3.93	1.90	3.70	3.40	2.49

c<sub>i</sub> = sampling cost on attribute i

$\bar{y}_i$  = average cutoff level on attribute i

$\sigma_i^2$  = sample variance

TABLE 24. Complete summary Results for Three-Attribute Unequal Intervals Problems: Means and Variances of Observed Cutoff Levels

$$3.B: \sum X_1 = [0,5], \sum X_2 = [0,10], \sum X_3 = [0,10]$$

#	N	c <sub>1</sub>	c <sub>2</sub>	c <sub>3</sub>	$\bar{y}_1$	$\bar{y}_2$	$\bar{y}_3$	$\sigma_1^2$	$\sigma_2^2$	$\sigma_3^2$
MTSAC										
1	33	.10	.10	.10	2.55	3.50	3.73	1.81	4.65	7.87
2	32	.75	.10	.10	2.40	3.74	2.96	1.65	6.13	6.32
3	33	.10	3.50	.10	2.58	2.71	3.16	2.01	4.61	6.60
4	32	.10	.10	3.50	2.52	3.25	2.63	1.53	4.16	5.59
PCC										
1	30	.10	.10	.10	2.76	4.11	4.15	1.82	8.53	9.32
2	30	.75	.10	.10	2.24	3.99	3.56	1.95	7.22	7.06
3	30	.10	3.50	.10	2.54	2.99	3.13	2.11	7.53	6.80
4	30	.10	.10	3.50	2.69	4.18	2.75	2.12	7.93	6.95
CSUN										
1	22	.10	.10	.10	3.11	4.90	3.78	2.22	7.69	7.79
2	21	.75	.10	.10	2.17	4.94	4.17	1.68	3.39	5.90
3	22	.10	3.50	.10	3.06	2.29	2.97	2.04	3.98	5.82
4	22	.10	.10	3.50	2.60	4.73	2.16	2.54	7.18	4.67
UCLA										
1	43	.10	.10	.10	3.06	5.23	4.38	1.66	5.93	6.05
2	43	.75	.10	.10	2.46	4.61	4.16	1.67	5.73	5.49
3	43	.10	3.50	.10	3.04	3.00	3.79	1.22	4.70	6.95
4	43	.10	.10	3.50	3.05	5.20	2.40	1.38	5.16	3.37

c<sub>i</sub> = sampling cost on attribute i

$\bar{y}_i$  = average cutoff level on attribute i

$\sigma_i^2$  = sample variance

TABLE 25: Counts Indicating Direction of Change in Cutoff Levels

Group	2A						2B					
	$\Delta y_1$			$\Delta y_2$			$\Delta y_1$			$\Delta y_2$		
	+	0	-	+	0	-	+	0	-	+	0	-
	$\Delta c_1 > 0$						$\Delta c_1 > 0$					
MTSAC	4	7	22	4	10	19	7	9	16	10	13	9
PCC	9	3	18	12	7	11	4	11	19	6	11	13
CSUN	1	1	20	11	3	8	2	2	18	6	5	11
UCLA	4	3	36	14	5	24	5	4	34	8	14	21
	$\Delta c_2 > 0$						$\Delta c_2 > 0$					
	7	12	14	4	8	21	12	10	10	10	13	9
	15	8	7	9	14	7	3	16	11	8	10	12
	11	2	9	3	3	16	6	10	6	1	4	17
	9	15	19	4	9	30	13	17	13	4	11	28

$c_i$  = sampling cost on attribute  $i$

$y_i$  = cutoff level on attribute  $i$

TABLE 26: Counts Indicating Direction of Change in Cutoff Levels

Group	3A									3B								
	$\Delta y_1$			$\Delta y_2$			$\Delta y_3$			$\Delta y_1$			$\Delta y_2$			$\Delta y_3$		
	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-
	$\Delta c_1 > 0$									$\Delta c_1 > 0$								
MTSAC	8	7	18	10	12	11	10	13	10	8	11	13	14	10	8	7	11	14
PCC	5	7	18	7	11	12	6	10	14	6	11	13	9	14	7	4	15	11
CSUN	1	3	18	6	6	10	7	5	10	1	3	17	6	7	8	8	6	7
UCLA	1	6	36	12	11	20	5	14	24	7	13	23	10	11	22	11	10	22
	$\Delta c_2 > 0$									$\Delta c_2 > 0$								
	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-
	$\Delta c_2 > 0$									$\Delta c_2 > 0$								
	$\Delta c_2 > 0$									$\Delta c_2 > 0$								
MTSAC	13	11	8	6	9	17	8	14	11	11	10	11	9	6	17	10	11	11
PCC	9	11	10	6	11	13	8	11	11	6	15	9	7	8	15	7	9	14
CSUN	5	9	8	4	0	18	6	5	11	6	8	8	0	4	18	3	7	12
UCLA	7	13	23	6	6	31	10	7	26	10	21	12	7	6	30	9	12	22
	$\Delta c_3 > 0$									$\Delta c_3 > 0$								
	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-
	$\Delta c_3 > 0$									$\Delta c_3 > 0$								
	$\Delta c_3 > 0$									$\Delta c_3 > 0$								
MTSAC	11	9	11	16	11	6	8	11	14	9	12	11	10	11	11	7	8	17
PCC	4	15	9	10	12	8	5	11	14	8	15	7	8	15	7	6	9	15
CSUN	6	9	7	6	5	11	2	4	16	3	8	11	9	7	6	3	5	14
UCLA	8	19	16	15	12	16	3	10	30	9	24	10	15	15	13	4	7	32

$c_i$  = sampling cost on attribute  $i$

$y_i$  = cutoff level on attribute  $i$

## INSTRUCTIONS

## PART ONE

This is part of a study in decisionmaking under uncertainty. During this session you will make several decisions. You will be paid at the end of the session and the amount you earn will depend on the decisions you make. Your decisions will determine rules for selecting items. The items will be of three different types: single-attribute items, two-attribute items, and some items with three attributes. At the end of the session one of your decisions will be chosen using the bingo cage, and you will be paid based upon the outcome of that decision. The basic tasks you will face for each type of item are similar so we shall start by explaining the single-attribute case.

Each single-attribute item is described by a number called the level of attribute 1. Whenever a single-attribute item is selected by the rule you determine, this number is the amount of money the experimenter will give you in exchange for that item. The rule you determine will select one item from a pool of potential items. Items differ only by their level of attribute 1. You will be told a range of possible values for the level of attribute 1. For example, "the level of attribute 1 will be at least 0 and less than or equal to \$10." Candidates from the pool of possible items will be generated by drawing balls from a bingo cage. The bingo cage contains balls numbered from 0 to 9. The way we shall use the cage to generate levels of attribute 1 is as follows: spin the cage until a ball comes

out—this determines the first (units) digit. Replace the ball in the cage and spin it again until another ball comes out—this determines the second (tens) digit, and so on if more digits are needed.

The rule for selecting an item in the single-attribute case is simple. You must choose a value for attribute 1, called the cutoff level for attribute 1. We will generate an item using the bingo cage. If that number is less than your cutoff level for attribute 1, the item is rejected and a new one is generated. This process continues until an item is selected which has a value for attribute 1 at least as large as your cutoff level for attribute 1. Each time a new item is generated, a fixed cost will be subtracted from your earnings, whether or not the item is accepted. Thus, the final payoff to you will be the value of the item selected by your rule minus the total cost of generating items. In other words, you will earn the value of the first number generated which exceeds or equals your cutoff level for attribute 1, less the cost of generating that number and all numbers that were rejected because they were below the cutoff level. Note that if you rejected such a large number of items that the total cost is greater than the value of the item, your earnings will be zero for that decision. You cannot lose money.

You will be given three pieces of information to help you determine your rule for the single-attribute case (i.e., to help you choose a cutoff level for attribute 1): the lowest and highest possible values for attribute 1, and the cost to you of each item generated by the bingo cage. For example, suppose that the first

seven items generated were below your cutoff level, but that the next one was above the cutoff. Your payment would be the amount of the last item generated (the eighth) minus eight times the cost of generating an item.

First, we shall ask you to select one individual as a monitor to watch the procedures, to examine the equipment, and to make sure that the the experimenters really are doing what they say they are doing. The monitor should check the truthfulness of what the experimenter says, but other than that may not communicate any information to you in any way. If the monitor communicates any other information, he or she will be asked to leave without payment. The monitor will receive \$\_\_\_\_\_.

(pick volunteer)

## INSTRUCTIONS

### PART TWO

The two-attribute problem is similar to the single-attribute problem. Two-attribute items are described by two numbers, a level of attribute 1 and a level of attribute 2. The rule for selecting a two-attribute item works much like that for selecting a single-attribute item. You must choose a cutoff level for attribute 1 and a cutoff level for attribute 2. As before, these will determine the smallest levels that you can receive for each attribute.

Once you have set cutoff levels for each attribute, we will begin searching for an item by generating levels for attribute 1 (again using the bingo cage). As before, we will generate items until one is found which has a level of attribute 1 in excess of your cutoff level for attribute 1. Each time an item is rejected and a new one is generated, you will be charged a fixed amount. Once an accepted level for attribute 1 has been found, we will generate a single level for attribute 2. You will also be charged a fixed amount for this, although it may differ from the cost for generating levels of attribute 1. If the level of attribute 2 is less than your cutoff level for attribute 2, the entire item will be rejected and a new item generated starting with attribute 1. In other words, if the level of attribute 2 is below your cutoff level, you must begin your search for an item with attribute 1—in the two-attribute problem, each attribute must exceed its cutoff level in order that the item be acceptable.

Otherwise, you start over. However, the costs for generating levels of each attribute will still be charged to you. Thus, your payoff in the two-attribute problem is the sum of the final values generated for each attribute, less the costs of generating all the numbers needed to find an accepted item.

Example:

1. Three draws required to get an accepted level of attribute 1.
2. First draw on attribute 2 below its cutoff level.
3. Five draws required to get another accepted level for attribute 1.
4. One draw for attribute 2, again below cutoff level.
5. Two draws needed to get new attribute 1.
6. One draw for attribute 2—above cutoff level—accepted.

Your payoff would be the last value generated at step 5 plus the value at step 6 minus ten times the cost of generating a first attribute (cost 1) minus three times the cost of generating a second attribute (cost 2).

## INSTRUCTIONS

### PART THREE

The three-attribute problem is nearly identical to the two-attribute problem. Now an item is described by three numbers, the levels for attributes 1, 2, and 3. You must choose cutoff levels for all three attributes and, for an item to be accepted, it must equal or exceed the cutoff on each of the three attributes. Before making your decision you will be told the minimum and maximum possible values for each attribute and the costs (which may vary across attributes and people) of generating attribute levels. Once you have set cutoff levels, we will begin searching for an item by generating levels for attribute 1 (again using the bingo cage). As before, we will generate items until one is found which has a level of attribute 1 in excess of your cutoff level for attribute 1. Each time an item is rejected and a new one is generated, you will be charged a fixed amount. Once an accepted level for attribute 1 has been found, we will generate a single level for attribute 2. You will also be charged a fixed amount for this, although it may differ from the cost for generating levels of attribute 1. If the level of attribute 2 is less than your cutoff level for attribute 2, the entire item will be rejected and a new item generated starting with attribute 1. If the value of attribute 2 is at least the cutoff level, we will generate a single level for attribute 3. If that value exceeds your cutoff, the item is complete and accepted. In other words, if the level of attribute 3 is below

## SAMPLE FORMS USED BY SUBJECTS

## ONE ATTRIBUTE

your cutoff level, you must begin your search for an item with attribute 1—in the three-attribute problem each attribute must exceed its cutoff level in order that the item be accepted. Otherwise, you start over. However, the costs for generating levels of each attribute will still be charged to you. Thus, your payoff in the three-attribute problem is the sum of the final values generated for each attribute, less the costs of generating all the numbers needed to find an accepted item.

Example:

1. Three draws required to get an accepted level of attribute 1.
2. First draw on attribute 2 below its cutoff level.
3. Five draws required to get another accepted level for attribute 1.
4. One draw for attribute 2, again below cutoff level.
5. Two draws needed to get new attribute 1.
6. One draw for attribute 2—above cutoff level—accepted.
7. One draw for attribute 3—rejected.
8. Four draws to get an accepted level of attribute 1.
9. One draw for attribute 2—accepted.
10. One draw for attribute 3—accepted.

Your payoff would be the last value generated at step 8 plus the value generated at step 9 plus the value at step 10 minus fourteen times the cost of generating a first attribute (cost 1) minus four times the cost of generating a second attribute (cost 2) and minus two times the cost of generating a third attribute (cost 3).

Name \_\_\_\_\_

Social Security No. \_\_\_\_\_

Subject Number \_\_\_\_\_

Decision No. \_\_\_\_\_

Attribute	Minimum Possible Value	Maximum Possible Value	Cost: C	Cutoff Level	Number of draws: N	Final Value: V
1						

Att.	V	-	C	x	N	=	earnings
1							

## TWO ATTRIBUTE

Name \_\_\_\_\_

Social Security No. \_\_\_\_\_

Subject Number \_\_\_\_\_

Decision No. \_\_\_\_\_

Attribute	Minimum Possible Value	Maximum Possible Value	Cost: C	Cutoff Level	Number of Draws: N	Final Value: V
1						_____ _____ _____
2						

Att.	V	-	C	x	N	=	earnings
1							
2							

Total Earnings (1 + 2)

## THREE ATTRIBUTE

Name \_\_\_\_\_

Social Security No. \_\_\_\_\_

Subject Number \_\_\_\_\_

Decision No. \_\_\_\_\_

Attribute	Minimum Possible Value	Maximum Possible Value	Cost: C	Cutoff Level	Number of Draws: N	Final Value: V
1						_____ _____ _____
2						_____ _____ _____
3						

Att.	V	-	C	x	N	=	earnings
1							
2							
3							

Total Earnings (1 + 2 + 3)



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